MULTI-DISCIPLINARY SENSING FOR PERSONAL EXPOSURE ASSESSMENTS: QUANTIFYING THE IMPACT OF TRAFFIC INTERVENTIONS AND METEOROLOGICAL VARIABILITY

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ABSTRACT

One of the main challenges of today's policy makers is to conduct evidence based decision making in order to proof the public that local environmental interventions are effective and efficient. Providing environmental information at a representative spatial and temporal granularity is challenging but indispensable to engage the general public in adopting new policies and by doing so, reach long-term environmental goals.

In prior work, a smart-city concept based on mobile monitoring of noise and air pollution illustrates the added value of a multidisciplinary approach [1,2]. Noise measurements act as a traffic proxy and provide traffic intensity and dynamics for air pollution models.
Simultaneous measurement campaigns covering all seasons, road types and meteorological conditions enable the disentanglement of changes at the source (traffic density and flow), impact of meteorology (wind speed) and the background pollution contribution. Pilot data from Belgium, New York City and India illustrated this noise-based exposure model in the past [3,4].

In this publication additional data collection illustrates the effectiveness and efficiency of mobile noise measurements for challenging smart city applications:

(1) Impact evaluation of traffic interventions on air pollution exposure

(2) Evaluation of effectiveness of alternative route choices

(3) Quantify the impact of emission policy measures on real-life cyclist exposure

1. INTRODUCTION

In 2017, in the vicinity of Antwerp, Belgium, a commuting exposure study evaluated the cyclist exposure to black carbon (BC), ultrafine particles (UFPs) and heavy metals along two different commuting routes over a period of three months in an 'air pollution only' approach [5].

In 2019, from July to October, we extended this dataset by measuring the spectral noise levels along the same routes without performing additional air pollution measurements. The collected mobile noise data was applied in the noise-based exposure model to predict the personal exposure of the cyclist to BC.
As a guidance for the reader, the structure of the simplified variant of the spatiotemporal noise-BC model is shown in the next equation:

$$\mathrm{BC_{tot}}(\mathrm{x,t}) = \mathrm{gamBC_{loc}}\left(\mathrm{L_{OLF}}(x), \mathrm{L_{HFmLF}}(x), \mathrm{StCan}(\mathrm{x}), \mathrm{WS}(\mathrm{t})\right) + \mathrm{BC_{amb}}(t) \quad (1)$$

Since no simultaneous measurements are performed in this pilot experiment, the noise components, engine noise (L_{OLF}) and cruising noise (L_{HFmLF}) are only known at a specific location x along the predesignated routes, along with the urban architecture, i.e. the street canyon index (StCan(x)). The collected traffic data is therefore identical for all individual trips of the high and low exposure route. The temporal variables are the wind speed (WS(t)) and the background BC concentration are trip specific. Function (1) is evaluated for each position (x) and time (t) with the spatial parameters insensitive to the time of the trip. We apply the model based on data collected in the city of Ghent in 2011.
Four exercises are performed by combining the BC model for Ghent 2011, the collected mobile noise data in 2019 and the BC exposure data collected during the air pollution campaign, collected in 2017 [5].

1.1 Impact of a traffic intervention

The mobile noise data in 2019 is collected from July until the beginning of October. The traffic conditions in July (holiday) are significantly different compared to September (working period). This difference is used as a virtual traffic intervention. The difference in traffic densities are quantified by comparing the noise data between the holiday (July) and post-holiday (September) period. The noise-BC-model based on the data from 2011 is used the evaluate the impact of this virtual traffic intervention.

1.2 Impact of route choice

Consequently a similar evaluation can be performed by comparing the impact of switching between low- and high exposure routes before and after this virtual intervention.

1.3 Retroactive evaluation of trip variability related to meteorological variation and changing ambient conditions

One of the advantages of the noise-based exposure model is the possibility to explain the contribution of background concentrations and the impact of wind speed on the resulting BC exposure. The pilot data can be used to validate this functionality by:

(1) applying the noise-based exposure model (Ghent 2011) to each individual trip in the 2017 campaign [5] including the actual background air pollution concentration and meteorological conditions.

(2) (2) subsequently comparing the actual measured BC exposure for each individual trip in 2017 with the model predicted values.

Notice that in this application, the mobile noise measurements provide the typical traffic condition, averaged within the chosen evaluation period. Variation in traffic throughout trips performed in the 2017 AQ campaign and a potential offset in the overall traffic situation between 2017 and 2019 is, evidently, not accounted for in this exercise. The potential change in noise emission of the fleet between 2017 and 2019 is part of the discussion.

1.4 Fleet emission changes between 2011 and 2017

The available noise-BC model dates from 2011, assessed shortly after the implementation of the Euro V legislation (2009). Diesel soot filters were introduced in the fleet and significant emission reductions were established. The 2011 model evaluated the fleet emission in a situation prior to the Euro V. For individual vehicles, under standardized conditions, a reduction of 90% was intended. In 2017, the majority of the diesel vehicles are equipped with diesel soot filters and the relative contribution of diesels in the fleet started to drop due to changes in the taxation of petrol and diesel fuel.

Comparing the measurements and predictions will give us some insights on the real-life exposure reduction for BC since the implementation of the Euro V legislation.

2. DATA COLLECTION

In our study, monitoring runs were performed along the two commuting routes evaluated in [5]; a low- (LE) and high-exposure (HE) route. Respective route distance was 9 and 8.4 km and spectral noise measurements were performed during both morning (~6:00–9:00 h) and evening (~15:00–19:00 h) rush hour periods, between 15/6/2019 and 10/10/2019(9 LE trips and 10 HE trips).

The collected noise measurements are a proxy for the changing traffic conditions. In the noise-exposure model, two noise attributes are relevant. In Figure 1, the distributions of both variables are presented for both the high and low exposure (HE vs LE) routes and the high and low traffic scenario (July vs Sept). The differences for engine noise (OLF) and cruising noise are statistically significant ($p < 0.001$) when switching from high to low exposure route in both traffic scenario's and also statistically significant ($p < 0.001$) for changes in traffic on the same route.

3. RESULTS

3.1 Traffic intervention

The traffic intervention is indirectly quantified by the mobile noise measurements. The BC exposure is a function of the traffic volume, the traffic dynamics, background concentration, wind speed and urban architecture (see formula 1).

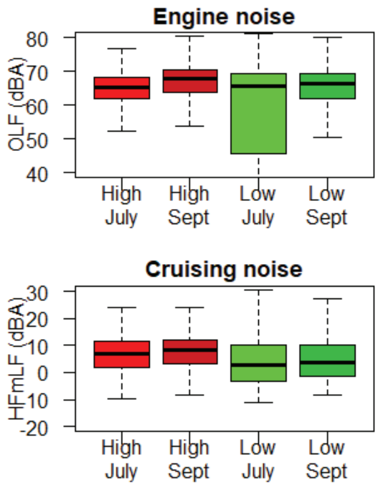

Figure 1. L_{OLF} (engine noise) and L_{HFmLF} (cruising noise) exposure distributions for all physical locations x along the predefined routes: high exposure route (HE; red), low exposure route (LE; green), presented separately for July and September.

To illustrate the method in a simplified way, the evaluation is performed for two different meteorological conditions: scenario 1 with wind speed of 2 m/s and background concentration of 1.5 µg/m^3 and scenario 2 with wind speed of 4 m/s and background concentration of 0.8 µg/m^3 (Figure 2). In a full implementation, a weighted average over all relevant meteorological conditions will give a fully integrated answer. The distributions of the BC exposure along the low and high exposure route are presented for the two meteorological conditions and for both traffic conditions.

In Table 2, the overall impact on the BC exposure is shown. The different meteorological conditions only have a minor impact on the resulting BC concentrations. The highest exposure reduction is achieved on the low exposure route (-33% vs -18%). The underlying rationale is that the relative change of the traffic density on the low exposure route is larger on roads with lower traffic volumes.

Reduction of traffic (Sept to July)			
	Scen 1	Scen 2	Mean
High	-17%	-19%	**-18%**
Low	-31%	-35%	**-33%**

Table 2. Evaluation of the traffic intervention.

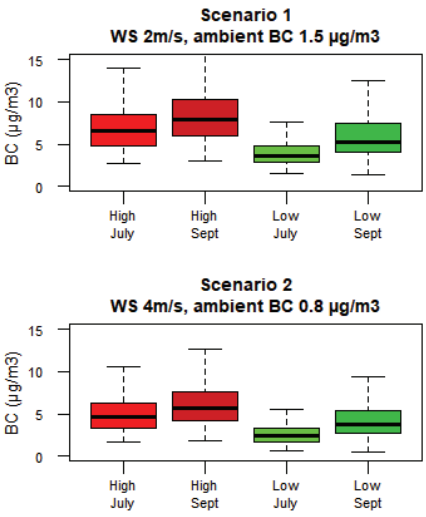

Figure 2. Modeled BC exposure along the predefined routes: high exposure route (HE; red), low exposure route (LE; green) and presented separately for July and September, the low and high traffic situation.

3.2 Impact of route choice

The inverse exercise, changing the route choice in fixed traffic conditions is presented in Table 3. The different meteorological conditions have a larger impact on the assessment compared to the traffic situation. This makes sense as the ventilation impact of wind will be higher on open bicycle highways (LE) when compared to street canyon like environments along the high exposure route (HE). This results in additional reductions in scenario 2, for both holiday (July) and post-holiday (Sep) period. The highest exposure reduction is achieved in the low traffic route (LE) (-41% vs -27%). The underlying rationale is similar to the previous exercise, overall traffic reductions have a relative higher impact on roads with lower traffic volumes.

Reduction due to route change: high to low			
	Scen 1	Scen 2	Mean
July	-39%	-43%	**-41%**
Sept	-26%	-29%	**-27%**

Table 3. Evaluation of the route choice intervention.

3.3 Retroactive evaluation of trip variability related to meteorological variation and changing ambient conditions

The noise-exposure model is applied to each individual trip performed in 2017 using the average noise levels (OLF and HFmLF) collected in September 2019 along the same two routes. The actual meteorological conditions and exhibited background concentrations (VMM R803) for each individual trip were used to simulate the exhibited exposure. A few assumptions have to be made in this exercise. First, we assume that the mobile noise assessment in September 2019 is representative for the traffic conditions in 2017. Secondly, we assume that the temporal behavior of the Antwerp background station (R803) is similar to the Antwerp monitoring station (40AL01) used to build the 2011 model in Ghent (no BC monitoring available in Ghent in 2011). This step was necessary since Black Carbon is no longer monitored in the station 40AL01, used in the Ghent 2011 model.

In this section we only evaluate the slope of the correlation between the measured BC exposure and the predicted BC exposure with the noise-based exposure model. The result is shown in Figure 3. The overall correlation for high and low exposure routes combined is 0.75. Splitting the correlation between low and the high exposure routes results in 0.84 and 0.78 respectively (Figure 4). Both correlations increase. The difference is related to the relative contribution of background and local traffic in the personal exposure of the bicyclist. The high exposure route is more sensitive to the traffic variable, the low exposure to the background concentrations. In both cases is the dominant variable – the traffic - properly assessed, despite the potential difference in traffic density and traffic dynamics between 2017 and 2019 since a small section of the LE route was not available due to road works during the 2019 campaign. The variation in personal exposure induced by to variation in wind speed and ambient concentrations is properly assessed.

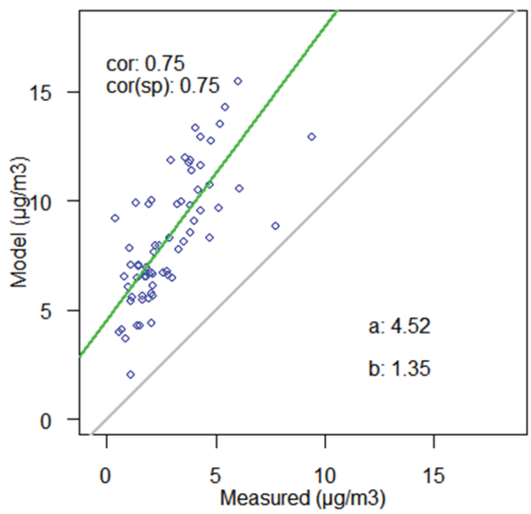

Figure 3. Association between model and measured BC exposure for each individual trip in 2017 (HE and LE combined).

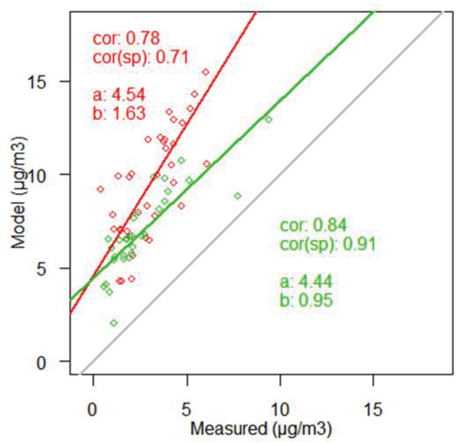

Figure 4. Association between model and measured BC exposure for each individual trip in 2017 (HE in red and LE in green).

Notice the overlap in the exposure assessments for both the high and low exposure route which illustrates the importance to be able to quantify the impact of wind and ambient conditions to evaluate alternative trajectories efficiently.

3.4 Fleet emission changes between 2011 and 2017

The most important application is the assessment of the real-life fleet emission changes over time. First, the relevant metric to evaluate the fleet emission change has to be defined. The trip-by-trip evaluation of the exposure prediction versus the actual measured exposure is the strongest candidate. This pilot study is however not sensitive to the individual traffic variation in the 2017 monitoring campaign. Trips with atypical traffic or significant specific events can disturb this assessment. The summary statistics of the exposure reduction illustrates this (Table 4). The minimum and maximum are rather extreme but in general, the trip-by-trip reduction is very stable (IQR of 14%). We can conclude that the cyclist exposure is reduced by about 67% over a period of six years. This observation is significantly higher than the overall reported 33% elemental carbon (EC) emission reductions between 2011 and 2017 in Flanders [6]. The overall reduction in EC combines multiple sources and is therefore less sensitive to evolution of the traffic contribution. This decrease acts as a minimum effect. When evaluating the reductions as a function of the diurnal pattern, much higher reductions are detected during rush hour and the closer the monitoring station to a high density road, the higher the reduction [7]. Several authors reflect on the differences between ambient and persona exposure methods and their findings are supported by comparing health impact studies [8]. The reduction of 67% can evaluated as realistic for real life exposure conditions for bicyclists since their exposure is predominantly linked to the emission change of the individual vehicles.

Min	Q1	Median	Mean	Q3	Max
-96%	-75%	-67%	-66%	-61%	-12%

Table 4. Evaluation BC fleet emission reduction based on the comparison of the measured (fleet of 2017) and predicted trip exposure (fleet of 2011).

4. DISCUSSION

4.1 Limitations, efficiency and applicability

From a modeling and validation perspective, the presented results fulfill all requirements for an independent cross-validation: different time and space and enough spatial variation (urban, suburban and rural). The original model was built in 2011 in and near the city of Ghent, the BC exposure data in Antwerp was collected in 2017 and the mobile noise monitoring performed to connect both datasets was collected in 2019 for an intervention period (summertime traffic conditions) and the regular situation (September).

Nevertheless, the tested applications in this pilot intervention study have limitations and it is important to identify the origin of the limitations.

The difference between the traffic situation in July and September is a real-life situation and the physical traffic data is not available to perform the evaluation up to the level of actual traffic volumes. The traffic volume changes are different on different sections of the road network and the preselected routes from the underlying study [5] act as a (biased) sample of the traffic on the road network. The inherited experimental design of the underlying study limits the applicability of the conclusions. More random trips should be used to assess the overall impact. The observed reductions can only be communicated in that perspective.

More importantly, the applied methodology is not affected by the mentioned limitations of the pilot study. This exercise can be performed in any season, under any meteorological conditions and for any route. Especially the efficiency of the noise as a traffic proxy is a strong feature. This aligns with the conclusion in the original publication which quantified the number of required repeated measurements to assess the traffic situation to about four when assessing during rush hour conditions only [2]. The number of required repetitions in a standard air quality application was set to forty (40) to account for meteorological induced variability, temporal variability and single pollution events [5,10]. Note that the measurements in 2017 within two months to avoid the seasonal variability, which increase the relative efficiency of the noise based approach even further. Short-term traffic interventions can't be evaluated in the standard 'air pollution only' approach due to the lack of time to collect the required amount of data to resolve the meteorological bias in the data collection. Personal exposure assessments and traffic intervention measurements are currently always impacted by meteorological bias [11]. A robust methodology including an instantaneous assessment of the exposure to traffic is able to quantify and adjust for the meteorological bias. This improvement related to the inclusion of an instantaneous traffic attribute is acknowledged in a recent publication evaluating state-of-the-art spatiotemporal LUR model [12]. Instantaneous traffic assessments not only improve the model but this pilot study extends the applications towards local policy interventions. The variation in air pollution exposure over time is dominated by the effect of wind. In the spatiotemporal models the physical influence of wind enters the spatiotemporal models at least twice: directly though the wind speed variable and indirectly in the ambient concentrations. The interaction between ambient concentration, temperature, humidity and wind speed adds to the complexity. In [3], the overfitting due to the combination of wind speed, temperature, ambient concentration and humidity is clear and this overfitting reduced the statistical significance of the local traffic attribute when including all four attributes. In the noise-based approach, those four meteorological attributes are disentangled due to the local traffic assessment. This is the physical origin of the stability of the noise-based approach, resulting in a model with only five (5) parameters while many classical LURs use much larger sets of - often highly correlated - parameters [12]. Temperature, humidity and a portion of the impact of wind are resolved within the ambient concentration while the wind speed remains relevant in the local component by assessing the faster dilution of the exhaust plumes under high wind conditions which result in lower peak exposure. This very local physical effect is not quantified in standard approaches and is the origin of the lack of full sensitivity of the standard approaches to the meteorological conditions.

The real issue with standard LURs is that they entirely depend on qualitative third party traffic data. Little data of adequate quality is available for the local roads in general and similar data that can quantify the effect of local traffic intervention is even rarer. The cost to acquire this third party traffic data and the lack of control over the quality over time are both significant and have the potential to nullify the intended application and goals. Collecting the noise data is far more effective and spatially and temporally more resolving than any the third party traffic data. It provides an unprecedented spatiotemporal update rate for local policy applications in personal exposure assessments enabling global comparisons of legislation and policy affecting the fleet composition. The statement of the authors of [12] on the low general applicability of the noise-based approach is therefore countered by multiple arguments: higher efficiency, proven stability, international robustness in time and space, sensitivity to fleet composition in time and space across continent and the newly added value through this pilot study: evaluating local interventions and fleet emission changes over time.

4.2 Potential noise emission variation

In the prior evaluation, the potential impact of the changing fleet composition and the road surface on the noise emission is neglected. The model quantifies the traffic through the engine noise and is by design largely insensitive to the rolling noise linked to the road surface. The engine noise can be affected by the long-term trend in vehicle fleet composition. The initial noise-based exposure model is based the 2011 fleet composition, which will be different in 2017. The fleet composition is mainly influenced by air pollution related EU regulations [7]. In contrast, the noise emission legislation didn't change significantly on individual vehicle level but the relative contribution of petrol, diesel, hybrid and electrical cars has changed due to the policy interventions.

Recurrent training of the noise-BC model using simultaneous noise and BC measurements is necessary to update the association between fleet composition, the associated noise emissions and resulting BC exposures [3]. For air pollution applications, the noise proxy for traffic is only a transformation layer, the absolute values are not relevant in this context.

The mobile noise monitors are calibrated. Technically the data can be used to extract trends over time but local policy interventions complicate these type of applications. Fixed noise monitoring stations would be able to quantify the impact of a changing fleet composition on the overall noise emission and can act as a cross-reference to quantify the fleet noise emission changes in the mobile data. Sadly enough few long-term noise stations are available. A first step in that direction is available in the processing of a noise monitoring near a highway in Flanders where the impact of the COVID-19 pandemic on the traffic emission was quantified [13].

The impact on noise exposure itself is relevant as such but comparing the noise parameters directly between different models from different countries has to be performed with caution. This lies not within the scope of this publication but relevant applications on the health impact of noise while commuting are emerging [14]. More of these type of noise specific applications are expected in the near future and illustrate the multidisciplinary potential and the reusability of the mobile noise data even further.

5. CONCLUSIONS

This pilot experiment is within its limitations successful on every account: the noise proxy predicts variability within trips, for different routes and for different traffic conditions. Modeled trip exposure correlated significantly ($r=0.75$) with the actual measured data, although a general reduction of 67% was observed in the BC measurements which can be attributed to the changing fleet (2011 vs 2017). In order to implement the provided noise applications, we propose a smart city implementation using continuous simultaneous monitoring of air pollution and noise at fixed locations and in mobile context to build the integrated proxy models. Mobile low-cost noise (bicycle based) sensors map the spatial and temporal variability of the traffic and traffic dynamics and feed the personal exposure applications. The methodology is sensitive to meteorological conditions, ambient concentrations, route choice and local, city specific and regional interventions affecting fleet emission of both noise and air pollution. This setup provides a long-term, multidisciplinary and cost-efficient policy support tool with unprecedented spatial and temporal resolution.

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